Supervised Learning Applied to Air Traffic Trajectory Classification

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Motivation

- ✈ New airspace uses and challenges
- ✈ Need for autonomy
- ✈ Future autonomous Air Traffic Management (ATM) tools will rely on:
  - ✈ Aircraft states
  - ✈ Machine learning and reasoning

Research Objective

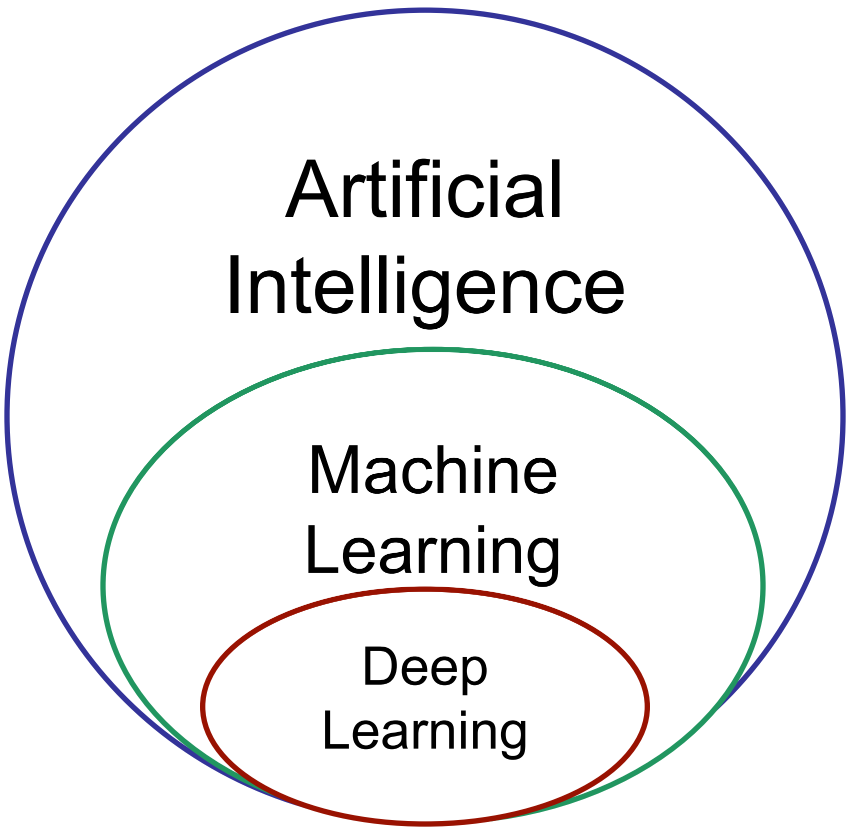
Explore supervised machine learning techniques in the context of aircraft trajectories to predict the landing runway.

Outline

- Background
- Problem Description
- Methodology
- Results
- Conclusion

Background

Hierarchy of Artificial Intelligence



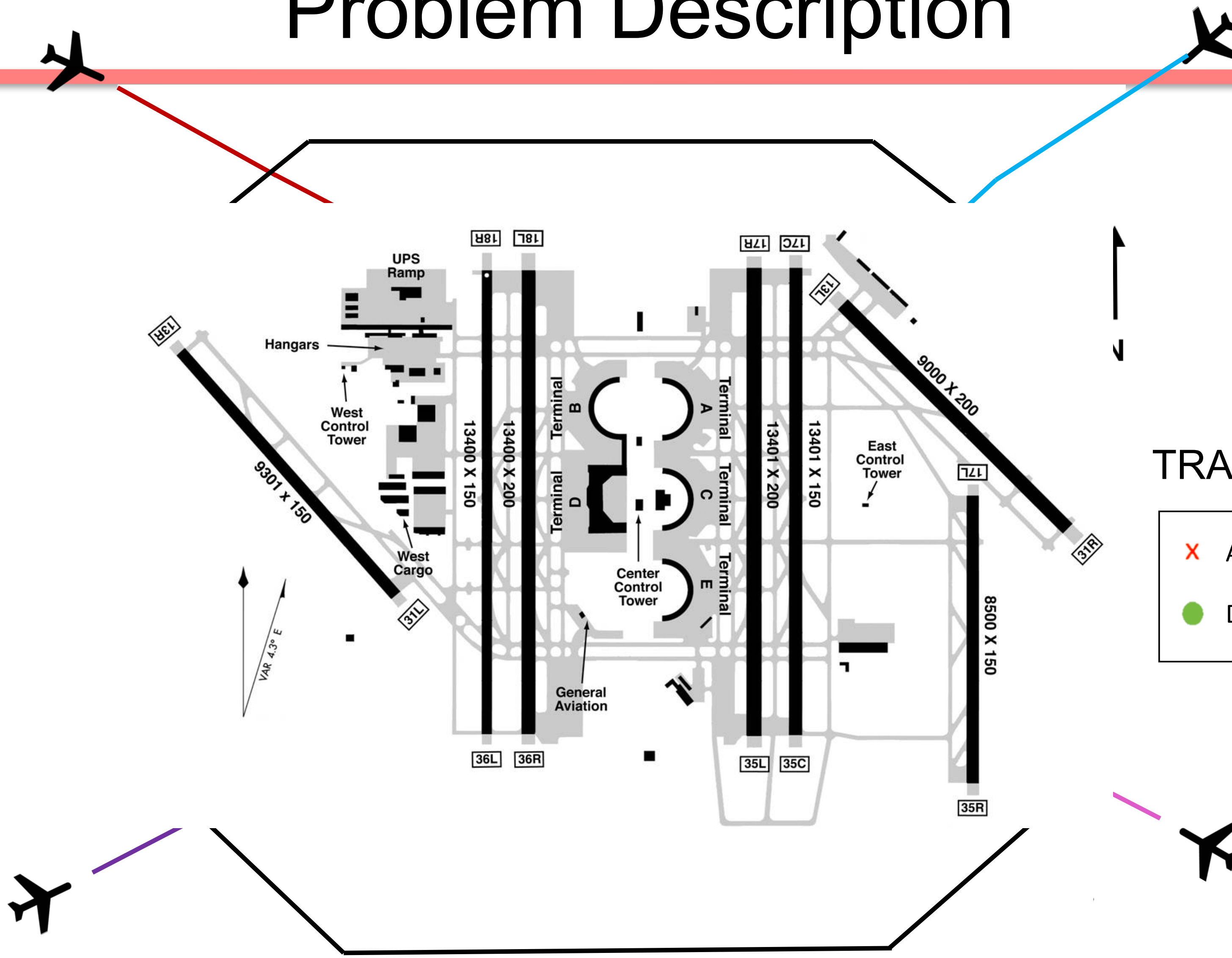
Background

- Applications of Machine Learning in ATM:
  - Air traffic delay prediction
    - Bayesian network [Xu et al., 2005]
    - Decision Trees, Random Forest, and K-Nearest-Neighbors [Choi et al., 2016]
  - Air traffic characterization
    - Clustering [Gariel et al., 2011][Conde Rocha Murça, 2016]
    - Reinforcement learning [Bloem and Bambos, 2015]
  - Air traffic reroute learning
    - Clustering [Arneson, 2015]
    - Data mining [Evans and Lee, 2017]
- Application of Deep Learning in ATM:
  - Flight delay prediction [Kim et al.,2016]

Background

- ATM benefits from Machine Learning
- Improvements of computational resources
- Need for autonomous systems
- Future autonomous ATM tools will rely on the predictions of future aircraft states

Problem Description



TRACON D10

X Arrival gates

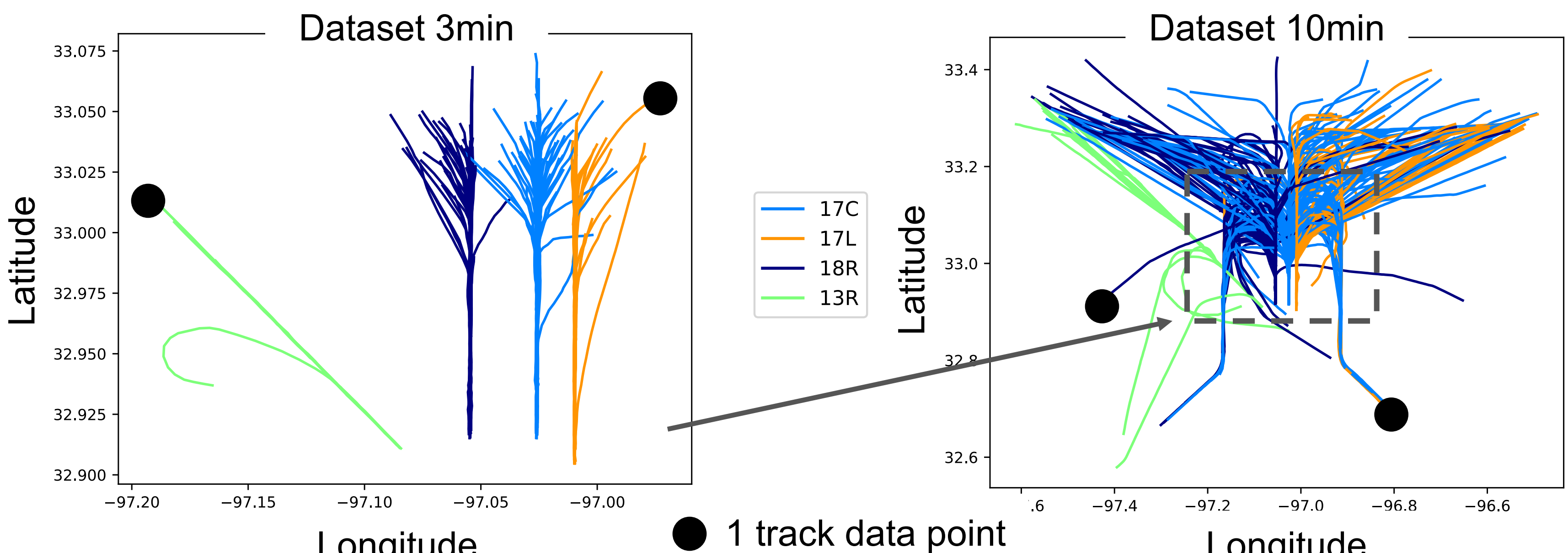
Departure gates

Problem Description

- Runway problem formulated as a trajectory classification study
  - Input: time series of aircraft states described by ten features
  - Output: landing runway
- Ten selected features
  - Airline
  - Aircraft weight class
  - TRACON entry location and entry time
  - Time steps of
    - Longitude, latitude, altitude
    - Ground speed, course angle, rate of climb

Methodology

- Data extraction
  - June 2017 DFW arrival flown tracks extracted from the NASA Ames Sherlock Data warehouse
  - 20,822 arrivals in South Flow configuration
- Two datasets are created using one track data point per trajectory, either 3 or 10 min away from landing into DFW



Methodology

Exploration of Machine Learning classification techniques

- Non neural network classifiers
  - Logistic Regression
  - Support Vector Machine
  - Bayes Classifiers
  - K-Nearest-Neighbors
  - Decision Trees
  - Ensemble Methods (bagging and boosting methods)

- Neural network classifiers
  - Multi-Layer Perceptron
  - Convolutional Neural Network

Methodology

- Computation pipeline
  - Preprocessing: data shuffling then K-Fold cross validation
  - Model computation: 21 models
    - 13 non neural network classifiers
    - 8 neural network classifiers
  - Post processing and results analysis

- Implementation: Python, Scikit-Learn and TensorFlow libraries

Results

Three analysis were conducted

- Prediction Analysis
- Sensitivity Analysis
- Feature Importance Analysis

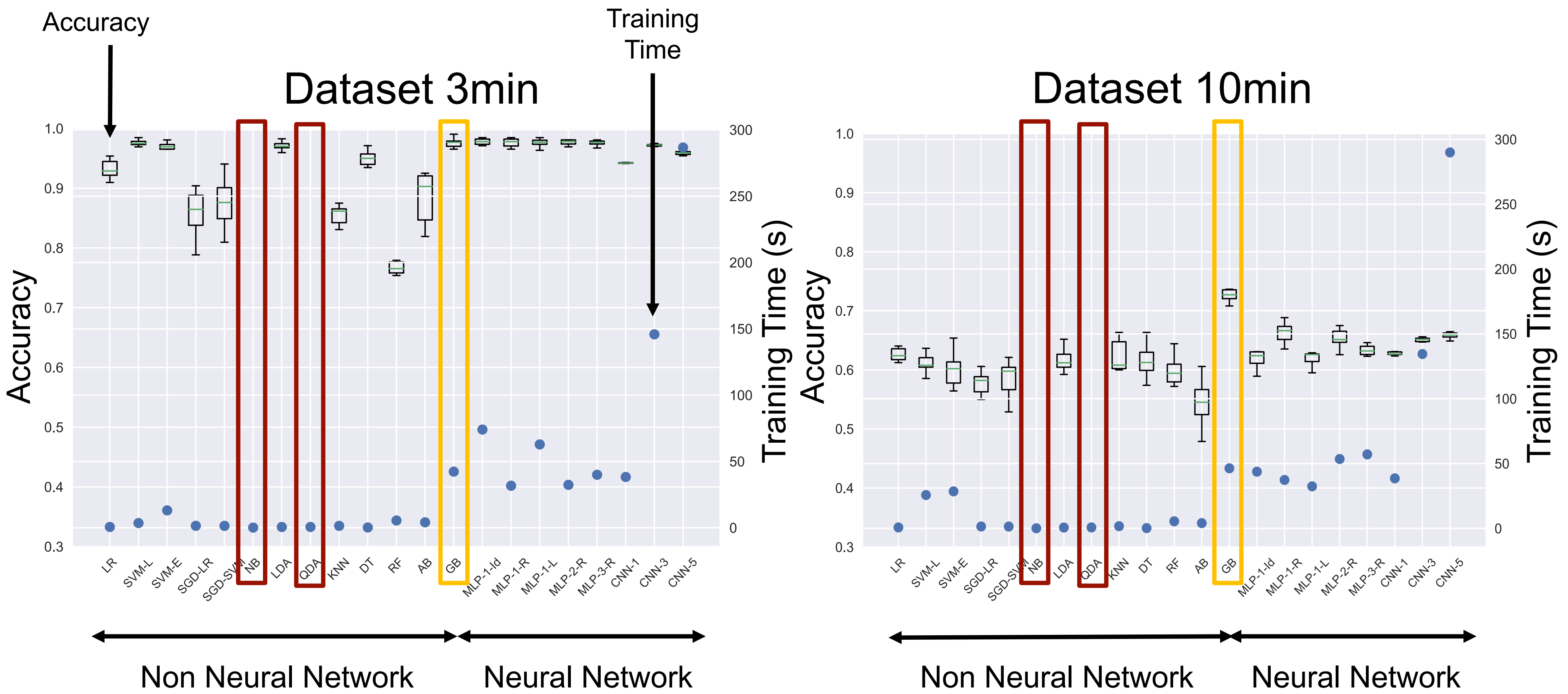
Prediction Analysis

- Objectives:
  - Can the landing runway be accurately predicted with the ten selected features and one track data point per trajectory?
  - How close to the runway must that point be to obtain accurate predictions?

- Results:

Trend	Dataset 3min	Dataset 10min
Accuracy	19.3% to 97.7%	10.9% to 73.2%
Training times	0.12s to 286.7s	0.12s to 289.9s
Testing times	0.009s to 2.26s	0.002s to 8.7s

Prediction Analysis



Best classifier: Gradient Boosting

Worst classifiers: Bayes

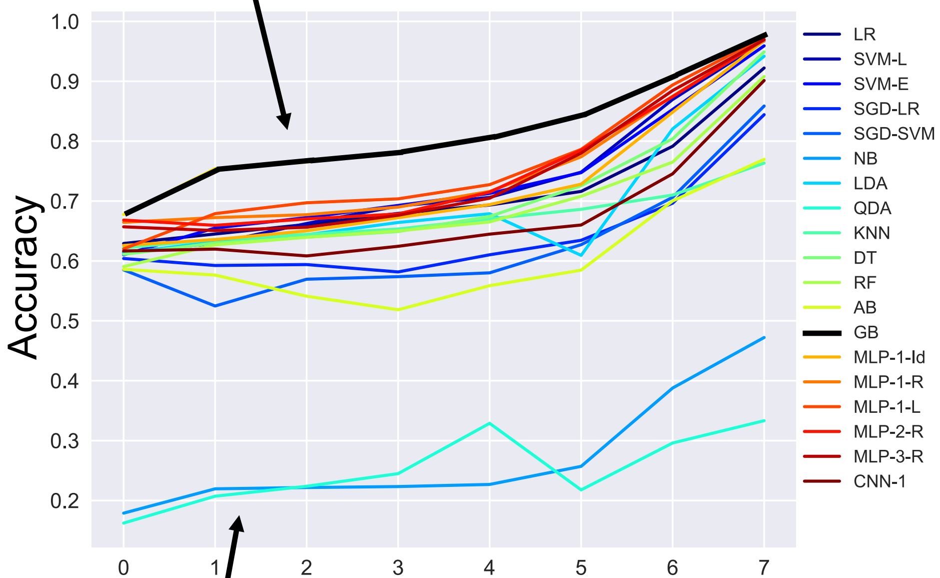
Sensitivity Analysis

- Objectives:
  - Can the prediction accuracy obtained with Dataset 10min be improved by training the classifiers using more time steps?
  - What is the sensitivity of each classifier with respect to the amount of time steps used in training?
- Process: start with Dataset 10min, increase the number of time steps to represent each trajectory during training

Sensitivity Analysis

Gradient Boosting

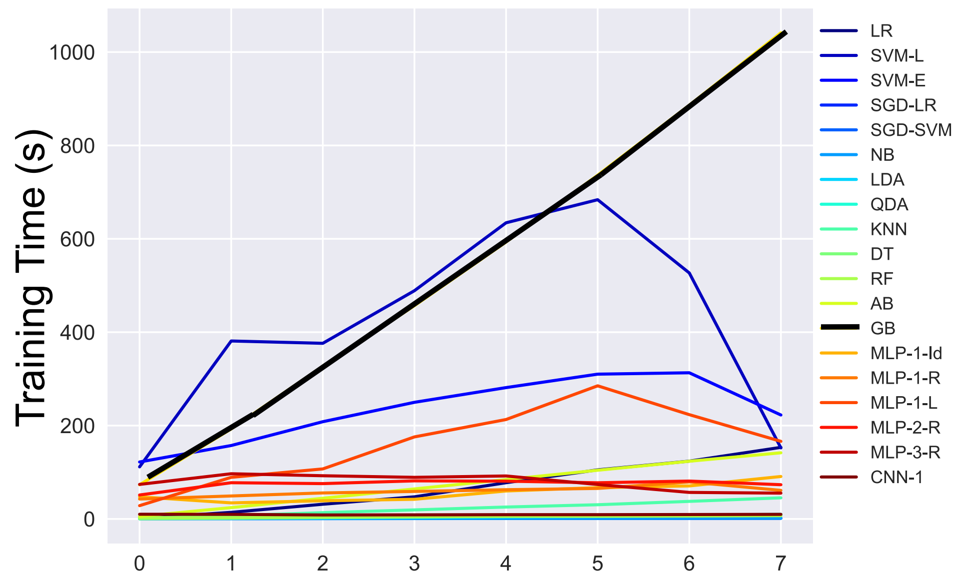
Accuracy



Minutes of Input Data

Bayes

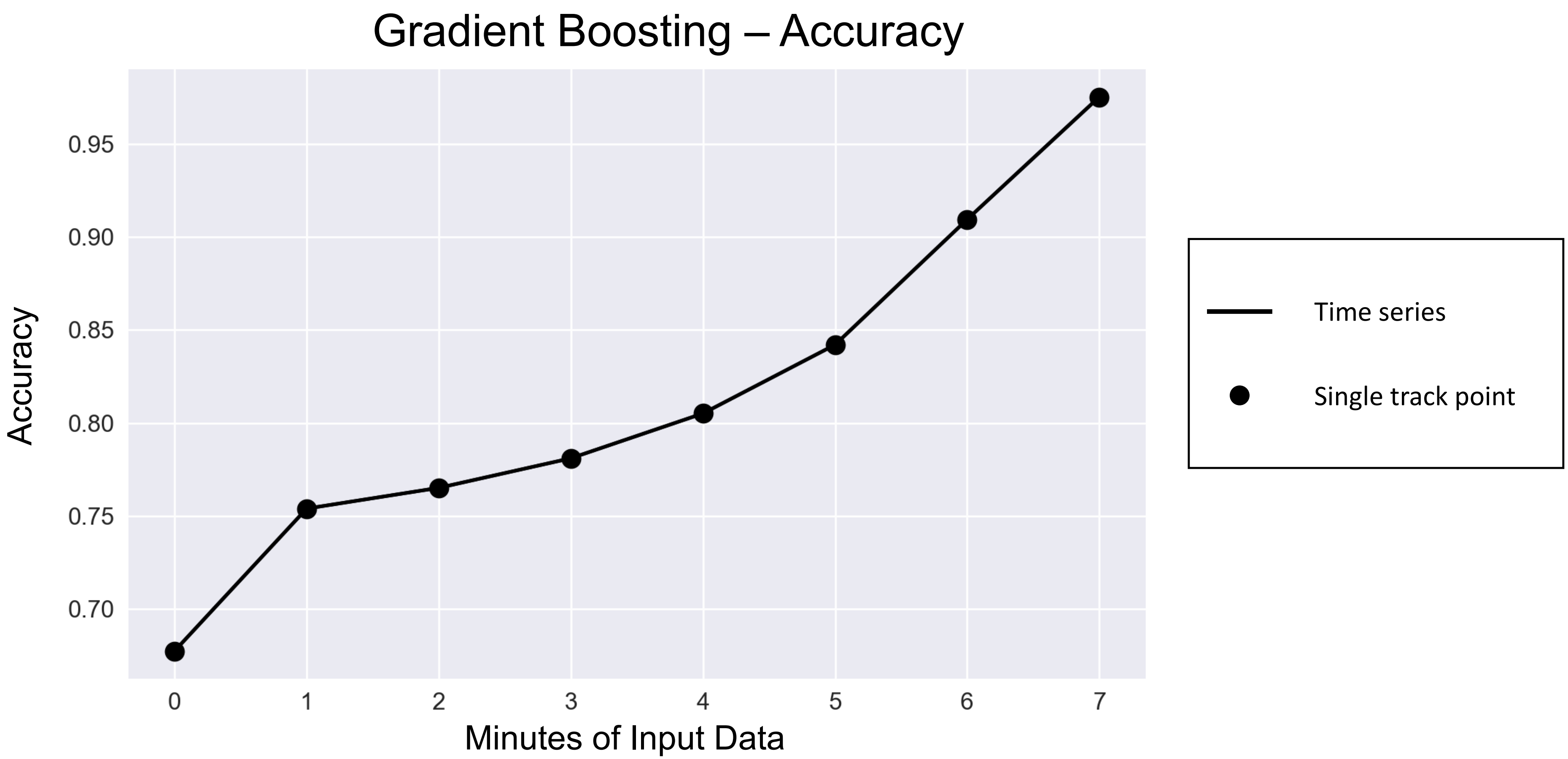
Training Time



Minutes of Input Data

Some classifiers are sensitive to the volume of input data

Sensitivity Analysis



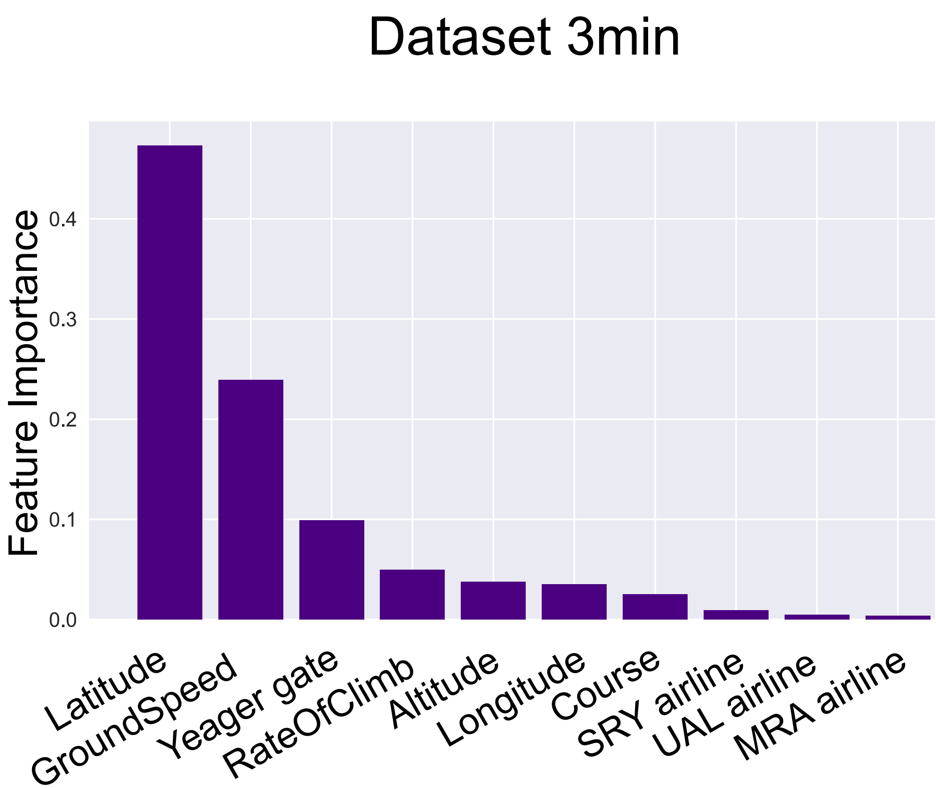
- The accuracy results are similar using one or more track data points during training
- The accuracy improvement depends on location not on the number time steps used during training

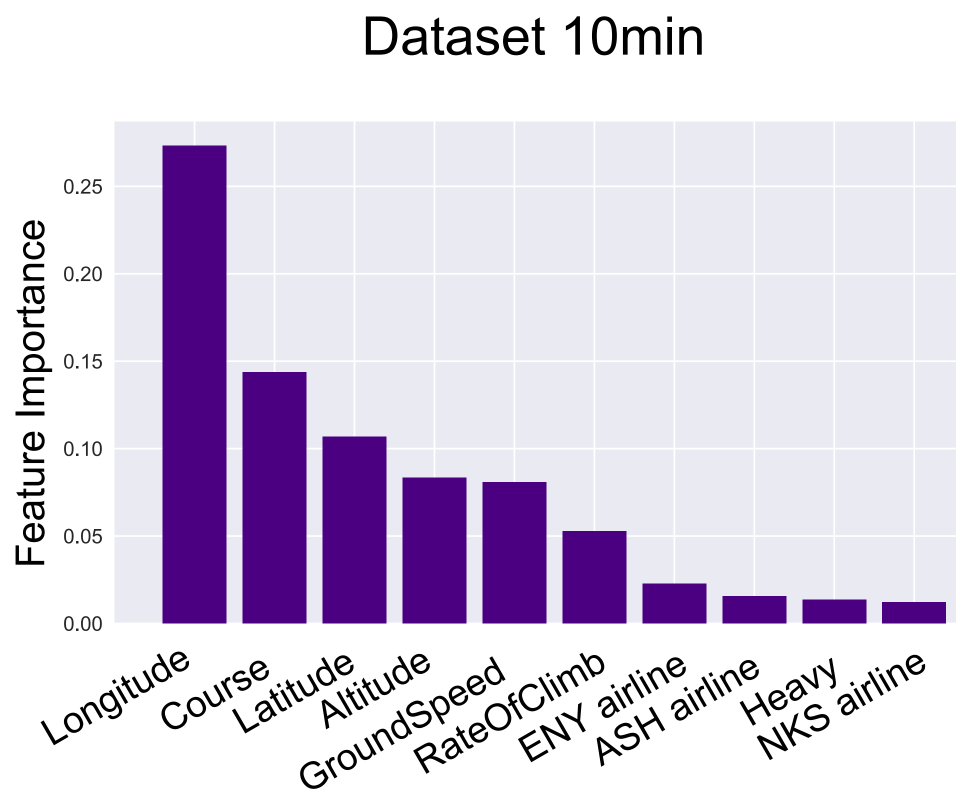
Feature Importance Analysis

- Objectives:
  – What are the most impactful features on the classification results?
  – Does the time step at which the analysis is performed influence the results?

- Process:
  – Gradient Boosting classifier is used
  – 2 cases are considered
    - Case Dataset 3min
    - Case Dataset 10min

Feature Importance Analysis





<u>Note</u>: results depends on the DFW airport geometry

Conclusion

- Exploration of Machine Learning techniques to solve a trajectory-runway classification problem
- Analysis results showed that
  - The different techniques perform differently to solve the problem
  - The closer to the runway the more accurate the landing predictions
  - Neural network models take longer to train than non neural network classifiers
  - Prediction accuracy results are similar whether one or more track data points are used as inputs for training
  - Some classifiers training times are sensitive to the amount of data used as input
  - For DFW, latitude and ground speed dominate 3min away from landing whereas longitude dominates 10min away from landing

Thank you!

Questions?

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